Noniterative Method to Approximate the Effective Load Carrying Capability of a Wind Plant

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***Abstract*—The effective load carrying capability (ELCC) is considered the preferred metric to evaluate the capacity value of added wind generation. However, the classical method of computing this metric requires substantial reliability modeling and an iterative process that is quite computationally intensive. Consequently, a noniterative method of estimating a wind plant's ELCC is proposed in this paper. Inspired by Garver's approximation and derived based on well-known reliability concepts, the proposed method provides an excellent approximation while requiring only minimal reliability modeling and no computationally-intensive iterative process. It computes ELCC estimates from a single function using only the wind plant's multistate probabilistic representation and a graphically determined parameter that characterizes the existing power system. After presenting the complete mathematical derivation of this function, the method is applied to compute the ELCC estimates of various wind plants at different penetration levels. It is shown that the resultant ELCC estimates only slightly overestimate the classically computed values by relative errors of 2.5% or less. Furthermore, the proposed method yields more accurate ELCC estimates than the capacity factor approximation, which is commonly used to approximate the ELCC of a wind plant.**

***Index Terms*—Approximation methods, capacity value, effective load carrying capability (ELCC), power generation planning, reliability, wind power generation.**

NOMENCLATURE

$C_{A,E,P}$	Nameplate capacity for the additional generation; existing and potential systems [megawatt].
C_j, p_j	Partial capacity outage states [megawatt] and corresponding individual probability.
COPT	Capacity outage probability table; $P(X_E > x)$ or $P(X_P > x)$.
COIPT	Capacity outage individual probability table; Table of C_j and p_j values of multistate unit.
E	Index for the existing system.
ELCC	Effective load carrying capability [percent].
k	Number of partial capacity outage states.
ΔL	Amount of extra load that can be served by the additional generation [megawatt].
L_i	Load demand condition [megawatt] of time duration t_i [e.g., hour].
LOLE	Loss-of-load expectation [days per year].
LOLP	Loss-of-load probability.
n	Number of t_i in the evaluation period [e.g., hours/year].
P	Index for the potential system.
$X_{E,P}$	Discrete random variable representing the possible capacity outage states of the existing and potential systems [megawatt].

Manuscript received September 17, 2007; revised September 17, 2007. This work was supported in part by the National Science Foundation under Grant ECCS-0725548. Paper no. TEC-00092-2007.

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Digital Object Identifier 10.1109/TEC.2008.918597

I. INTRODUCTION

SEVERAL studies have identified the effective load carrying capability (ELCC) as being the preferred metric to evaluate the capacity value of wind generation [1]–[4]. Although accurate, this metric requires substantial reliability modeling and an iterative process that is computationally intensive. Consequently, interest has emerged in proposing simpler methods to approximate a wind plant's ELCC. These simpler methods can be especially useful when performing preliminary investigation of wind generation expansions. The noniterative method proposed in this paper requires minimal reliability modeling and is less computationally intensive than the classical ELCC computing method.

Various risk-based and time-period-based approximation methods have been proposed to estimate a wind plant's ELCC [1]–[4]. Among the risk-based methods is Garver's approximation, a graphical method of estimating the ELCC of conventional generating units [5]. This approximation is mathematically derived using a two-state representation to model the additional conventional unit. Although modeling a generating unit as being either fully ON or fully OFF is appropriate for conventional generation, it is not well suited for variable output generation. Therefore, the novel method introduced in this paper is adapted from Garver's approximation but models the additional unit with a multistate representation. As for Garver's approximation, the proposed method uses a graphically-determined parameter and is based on known reliability probabilistic concepts such as capacity outage probability table (COPT), loss-of-load probability (LOLP), and loss-of load expectation (LOLE) [6].

Since the ELCC concept has been implemented in slightly different ways, we will start by defining the classical computing method used in this study. Then, we will derive the novel approximation method using known reliability probabilistic concepts. We will compare the classical and approximation methods by computing the ELCC of several wind plants at various penetration levels. Finally, our ELCC estimates will be compared to the wind plant's capacity factor, a current way of estimating the capacity value of wind generation [1].

II. Effective Load Carrying Capability of a Wind Plant: A Classical Computing Method

In generation expansion studies, when a new generating unit is to be added to an existent power system, the effective load carrying capability (ELCC) of this unit will be the amount of extra load that can be served while keeping a designated level of reliability. The designated level is usually the loss-of-load expectation (LOLE) of the system before the addition of the new generating unit. It assumes the existing system is already well planned. Therefore, when equating the LOLEs of the existing and potential systems, the concept of ELCC is classically represented by the following expressions

$$\mathrm{LOLE}_E = \mathrm{LOLE}_P$$

or

$$\sum_{i=1}^{n} P(X_E > C_E - L_i) \times t_i = \sum_{i=1}^{n} P(X_P > (C_E + C_A) - (L_i + \Delta L)) \times t_i \qquad (1)$$

where ΔL is the extra load that can be served by the additional generation. $P(X_E > C_E - L_i)$ and $P(X_P > (C_E + C_A) - (L_i + \Delta L))$ are the loss-of-load probabilities (LOLPs) of the existing and potential system. These LOLPs represent the probabilities of having a capacity outage greater than $C_E - L_i$ and $(C_E + C_A) - (L_i + \Delta L)$, the conditions when a loss of load would occur in each system. The cumulative probabilities $P(X_E > x)$ and $P(X_P > x)$ are obtained from each system's capacity outage probability table (COPT). This table models the system's generation reliability.[1] Due to the discrete nature of the resultant LOLPs, (1) is best solved iteratively. Consequently, multiple LOLE calculations must be performed for various values of ΔL before the correct value resulting in the chosen LOLE is found. Note that this iterative process is, in part, what makes the ELCC metric a computationally-intensive calculation.

Once (1) is solved for ΔL, the ELCC of the additional generator is usually expressed as the percentage of the extra load over the added generator's nameplate capacity

$$\mathrm{ELCC} = \frac{\Delta L}{C_A} \times 100\%. \qquad (2)$$

The classical method of implementing the ELCC concept described in this section can be altered depending on how wind generation is integrated to the power system's reliability model. Essentially, there are two ways of integrating wind generation into the model: the multistate (or prospective) approach and the load adjustment (or retrospective) approach [1]. While the load adjustment approach integrates wind as a negative load, the multistate approach takes a more probability-oriented perspective. In this approach, wind generation is incorporated in the potential system's COPT as a multistate unit that can exist in one or more partial capacity outage states. Since the proposed method models wind as a multistate generating unit, to give better grounds for comparison, the multistate approach will also be used when classically computing the ELCC of a wind plant. In doing so, the classical computing method can be applied as described in this section with no alterations.

[1] [6] gives a good review on the reliability concepts of COPT, LOLE, and LOLP.

III. Effective Load Carrying Capability of a Wind Plant: A Non-iterative Computing Method

A. Basis

Garver's approach [5] proposed a way to simplify ELCC calculations for conventional generation. Indeed, the ELCC of an additional conventional unit was approximated using graphical aids and a graphically-determined parameter. This parameter characterized the existing system's loss-of-load probability as a function of reserve and reduced the number of reliability calculations needed. Although the approximation focused on the graphical aids, the most interesting aspect about this method was the mathematically derived function used to create these graphs: from a simple equation one could obtain an accurate ELCC estimate. The derivation of this function was based on well-known probability concepts, but, unfortunately, modeled the additional unit with a two-state representation. Although this representation is appropriate for conventional generation, modeling wind generation by being either fully ON or OFF is not an adequate representation. Therefore, using an analogous approach, a function estimating the ELCC of variable output generation was developed while modeling this generation with a more appropriate multistate representation.

Similar to Garver's expression, our derived function is based on well-known probability concepts and uses the additional unit's reliability characteristics as well as a graphically-determined parameter. Our parameter, however, characterizes the existing system's loss-of-load probability as a function of load demand. The first step to our method consists of determining this parameter.

B. Graphical Parameter

The graphical parameter is obtained from a plot that illustrates how the existing system's LOLE changes for an increase or decrease in load demand. First, different load duration curves are created as variants of the system's typical load demand. They are produced by positively or negatively shifting the typical load duration curve. Consequently, each new curve has the same overall variability as the typical load duration curve (e.g., summer and winter peaks). The shift is chosen as a percentage of the typical peak load. Each load duration curve is computed using the following expression:

$$L_c = L_t \pm c \cdot L_{t_{\mathrm{pk}}} \qquad (3)$$

where L_c is a new load duration curve, L_t is the typical load duration curve with peak load $L_{t_{\mathrm{pk}}}$, and c is a percentage. The existing system's LOLE is then computed for each new load demand. Subsequently, the resulting LOLE values are plotted as a function of the typical and new load duration curves. In this graph, all load duration curves are represented by their peak load; although the actual LOLE calculation is performed using the whole curve. Once these results are plotted, the data points are curve-fitted with an exponential relationship.[2] The relationship abides by the following equation

$$\mathrm{LOLE}_{L_{\mathrm{pk}}} = B \times e^{m \times L_{\mathrm{pk}}} \tag{4}$$

where L_{pk} is the peak load of the load duration curve, B is the pre-exponential coefficient, and m is defined as the system's graphical parameter with units of MW^{-1}. The value of the m parameter is determined by any exponential curve fitting method. The derivation will unveil that the B parameter is inconsequential to this analysis. Along with basic probability concepts of reliability theory [6], the exponential relationship will be used to mathematically derive an ELCC estimating function for variable output generation. The steps of this derivation are presented in the next section.

C. Mathematical Derivation

When an additional variable output generator is modeled as a multistate unit, the COPT of the potential system after the addition of this new generating unit can be represented by the following cumulative probabilities $P(X_P > x)$:

$$P(X_P > x) = \sum_{j=1}^{k} p_j \times P(X_E > x - C_j) \tag{5}$$

where $P(X_E > x - C_j)$ represents the existing system's cumulative probability of having a capacity outage greater than $(x - C_j)$. This cumulative probability is obtained from the COPT of the existing system.

Given a particular load duration curve identified by its peak load L_{pk}, the LOLE of the potential system can be expressed as

$$\mathrm{LOLE}_{P,L_{\mathrm{pk}}} = \sum_{i=1}^{n} P(X_P > C_P - L_i) \times t_i \tag{6}$$

where $P(X_P > C_P - L_i)$ is the LOLP for the load condition L_i of duration t_i and n is the number of t_i in the chosen evaluation period.

Since the term $P(X_P > C_P - L_i)$ in (6) is equivalent to the term $P(X_P > x)$ in (5), when x equals $C_P - L_i$, it can be replaced by

$$P(X_P > C_P - L_i) = \sum_{j=1}^{k} p_j \times P(X_E > C_P - L_i - C_j). \tag{7}$$

This substitution enables the LOLE of the potential system to be expressed as a function of the existent system's COPT rather than its own COPT. After expanding the summation term in (7) and substituting in (6), this equation becomes

$$\begin{aligned}\mathrm{LOLE}_{P,L_{\mathrm{pk}}} = \sum_{i=1}^{n} [&p_1 \times P(X_E > C_P - L_i - C_1) \\ &+ p_2 \times P(X_E > C_P - L_i - C_2) \ldots \\ &+ p_k \times P(X_E > C_P - L_i - C_k)] \times t_i.\end{aligned} \tag{8}$$

[2]Garver suggested that an exponential relationship could accurately approximate how a power system's LOLE responds to a shift in load demand [5].

The total capacity of the potential system C_P is equivalent to the total capacity of the existing system C_E plus the nameplate capacity of the added unit C_A; therefore, (8) can be rewritten as

$$\begin{aligned}\mathrm{LOLE}_{P,L_{\mathrm{pk}}} = \sum_{i=1}^{n} [&p_1 \times P(X_E > C_E + C_A - L_i - C_1) \\ &+ p_2 \times P(X_E > C_E + C_A - L_i - C_2) \ldots \\ &+ p_k \times P(X_E > C_E + C_A - L_i - C_k)] \times t_i.\end{aligned} \tag{9}$$

By rearranging and distributing the summation, (9) becomes

$$\begin{aligned}\mathrm{LOLE}_{P,L_{\mathrm{pk}}} &= p_1 \times \sum_{i=1}^{n} [P(X_E > C_E - (L_i + C_1 - C_A))] \times t_i \\ &+ p_2 \times \sum_{i=1}^{n} [P(X_E > C_E - (L_i + C_2 - C_A))] \times t_i \ldots \\ &+ p_k \times \sum_{i=1}^{n} [P(X_E > C_E - (L_i + C_k - C_A))] \times t_i.\end{aligned} \tag{10}$$

Each one of the k summation terms in (10) is equivalent to the existing system's LOLE computed for a load duration curve with a peak load value of $L_{\mathrm{pk}} + C_j - C_A$. In turns, each of these k load duration curves is equivalent to a load duration curve of peak load L_{pk}, which is shifted by adding a constant $C_j - C_A$; this constant is added to each hourly load data L_i. From this observation, (10) is rewritten as

$$\begin{aligned}\mathrm{LOLE}_{P,L_{\mathrm{pk}}} &= p_1 \times \mathrm{LOLE}_{E,L_{\mathrm{pk}}+C_1-C_A} \\ &+ p_2 \times \mathrm{LOLE}_{E,L_{\mathrm{pk}}+C_2-C_A} \ldots \\ &+ p_k \times \mathrm{LOLE}_{E,L_{\mathrm{pk}}+C_k-C_A}.\end{aligned} \tag{11}$$

Because of the shifted change in the load duration curve, each $\mathrm{LOLE}_{L_{\mathrm{pk}}+C_j-C_A}$ term in (11) can be replaced by its respective exponential approximation using (4) and the equation becomes

$$\begin{aligned}\mathrm{LOLE}_{P,L_{\mathrm{pk}}} &= p_1 \times B \times e^{m \times (L_{\mathrm{pk}}+C_1-C_A)} \\ &+ p_2 \times B \times e^{m \times (L_{\mathrm{pk}}+C_2-C_A)} \ldots \\ &+ p_k \times B \times e^{m \times (L_{\mathrm{pk}}+C_k-C_A)}.\end{aligned} \tag{12}$$

Using exponential identities, $B \times e^{m \times L_{\mathrm{pk}}}$ is isolated and replaced by (4) so that (12) can be rewritten as

$$\begin{aligned}\mathrm{LOLE}_{P,L_{\mathrm{pk}}} = \mathrm{LOLE}_{E,L_{\mathrm{pk}}} \times [&p_1 \times e^{m \times (C_1 - C_A)} \\ &+ p_2 \times e^{m \times (C_2 - C_A)} \cdots + p_k \times e^{m \times (C_k - C_A)}].\end{aligned} \tag{13}$$

The concept of ELCC described in Section III comes into play. Recall that the ELCC of an additional generator represents the extra load that can be served while keeping the designated level of reliability, usually the LOLE of the existing system calculated with its typical load duration curve. Therefore, we can express this as

$$\mathrm{LOLE}_{P,L_{t_{\mathrm{pk}}}+\Delta L} = \mathrm{LOLE}_{E,L_{t_{\mathrm{pk}}}} \tag{14}$$

where $L_{t_{\mathrm{pk}}} + \Delta L$ is the typical load duration curve to which is added a constant extra load ΔL to each hourly load data.[3] Contracting the $p_j \times e^{m\times(C_j - C_A)}$ terms and replacing the general load duration curve L_{pk} by the specific load duration curve $L_{t_{\mathrm{pk}}} + \Delta L$, (13) is rewritten as

$$\mathrm{LOLE}_{P,L_{t_{\mathrm{pk}}}+\Delta L} = \mathrm{LOLE}_{E,L_{t_{\mathrm{pk}}}+\Delta L} \times \sum_{j=1}^{k} p_j \times e^{m\times(C_j - C_A)}. \tag{15}$$

Using (4), (15) becomes

$$\mathrm{LOLE}_{P,L_{t_{\mathrm{pk}}}+\Delta L} = B \times e^{m\times(L_{t_{\mathrm{pk}}}+\Delta L)} \times \sum_{j=1}^{k} p_j \times e^{m\times(C_j - C_A)}. \tag{16}$$

Once again, using exponential identities, (16) is rearranged as

$$\mathrm{LOLE}_{P,L_{t_{\mathrm{pk}}}+\Delta L} = B \times e^{m\times L_{t_{\mathrm{pk}}}} \times e^{m\times \Delta L} \times \sum_{j=1}^{k} p_j \times e^{m\times(C_j - C_A)} \tag{17}$$

which finally reduces to

$$\mathrm{LOLE}_{P,L_{t_{\mathrm{pk}}}+\Delta L} = \mathrm{LOLE}_{E,L_{t_{\mathrm{pk}}}} \times e^{m\times \Delta L} \times \sum_{j=1}^{k} p_j \times e^{m\times(C_j - C_A)}. \tag{18}$$

Applying the ELCC concept given by (14), (18) becomes

$$1 = e^{m\times \Delta L} \times \sum_{j=1}^{k} p_j \times e^{m\times(C_j - C_A)}. \tag{19}$$

Finally, the natural logarithm is taken on both sides of the equation to isolate ΔL and we obtain the ΔL estimating function

$$\Delta L = \frac{1}{m} \times \left[-\ln \left[\sum_{j=1}^{k} p_j \times e^{m\times(C_j - C_A)} \right] \right]. \tag{20}$$

Using (2) and (20), the ELCC of an additional multistate unit of nameplate capacity C_A modeled by k possible capacity outage states C_j with corresponding individual probability p_j can now be estimated given the existing power system's m parameter

$$\mathrm{ELCC} = \left[-\ln \left[\sum_{j=1}^{k} p_j \times e^{m\times(C_j - C_A)} \right] \right] \times \frac{100\%}{m \times C_A}. \tag{21}$$

Note that (21) can also be used for two-state units whose unavailability is represented by their forced outage rate (FOR). Indeed, for a two-state unit of capacity C_A, there exist two possible capacity outage states C_j. Since two-state units are either fully ON or fully OFF, we can replace C_1 by 0, p_1 by $(1 - \mathrm{FOR})$, C_2 by C_A, and p_2 by FOR. Equation (21) is, therefore, reduced to

$$\mathrm{ELCC} = [-\ln[(1 - \mathrm{FOR}) \times e^{-m\times C_A} + \mathrm{FOR}]] \times \frac{100\%}{m \times C_A}. \tag{22}$$

This expression is analogous to Garver's approximation although the m parameter and risk basis are different.

IV. Case Study

In this section, the noniterative approximation will be applied in a case study. The resultant ELCC estimates will be compared to the classically computed values as well as to the capacity factor, a common ELCC estimate.

A. Existing System Reliability Model

The existing system used in this case study is based on a realistic power system; it consists of 16 conventional generating units ranging from 22 to 555 MW and has a total nameplate capacity of 2728 MW. For the scope of this analysis, we consider all generators to be base-load units that are committed during the full year. Each generator is modeled with the two-state representation of being either fully ON or fully OFF and its unavailability is expressed by its FOR. The North American Electric Reliability Council "Generating Availability Data System" provided relevant FOR values for the various types of generators and generator capacities [7]. Using the generator capacities along with the corresponding FOR values, the generation reliability model of the existing system, or COPT, was built following the basic probability theories in [6]. The resultant COPT is composed of 1721 possible capacity outage states and provides the cumulative probability associated with a capacity outage greater than a determined value. The various wind plants described in the following section will be added to this existing power system.

B. Wind Generation Reliability Model

As mentioned previously, the multistate unit approach is used to model the variable nature of wind generation. This approach consists of representing the wind plant as a multistate unit that can exist in one or more partial capacity outage states C_j with corresponding individual probability p_j. From applying this approach, a capacity outage individual probability table (COIPT) is created to represent the wind plant. The COIPT consists of the individual probability of having a capacity outage equal to a determined value. The COIPT is built at a chosen resolution described as the number of megawatt between two capacity outage states. The lower the resolution, the greater the number of partial output states, and the better the wind plant is modeled. For example, at a resolution of 2 MW, a 20 MW wind plant would be modeled by 11 partial capacity outage states: $C_1 = 0$ MW, $C_2 = 2$ MW, ... $C_9 = 16$ MW, $C_{10} = 18$ MW, $C_{11} = C_A = 20$ MW. Using the wind plant's power output data, the individual probability p_j associated with the partial capacity outage state C_j is calculated by counting the number of occurences when the power output is equal to $C_A - C_j$ divided by the total number

[3]The typical load duration curve, which is positively shifted by ΔL.

of power output data points:[4]

$$p_j = \left[\frac{\#\text{ occurrences when power output is } C_A - C_j}{\text{Total } \#\text{ of power output data points}}\right]. \quad (23)$$

When a power output data point falls between two values of $C_A - C_j$, it is counted as an occurrence for the highest value. Ideally, the chosen resolution should be small compared to the wind plant's nameplate capacity so that this approximation has an insignificant impact on the final model.

In reality, multiple years of power output data should be used to build the COIPT of the studied wind plant. In this case study, only a full year of power output data from two different wind plants was available: WP-1 of 113 MW nameplate capacity and WP-2 of 230 MW nameplate capacity. Using this data, various scenarios were created to test our method. In order to demonstrate how the ELCC of a wind plant varies as its penetration level increases, various levels were obtained by simply scaling the actual power output data. The following equation was used

$$p_{C_A}(t) = \frac{p_{C_O}(t) \times C_A}{C_O} \quad (24)$$

where C_A is the desired total capacity in megawatt of the scaled wind plant (or the eventual additional generation), $p_{C_O}(t)$ is the power output in megawatt at time t of the original wind plant (WP-1 or WP-2) of capacity C_O (113 or 230 MW), and $p_{C_A}(t)$ is the power output in megawatt at time t of the scaled wind plant. In this study, the penetration level is defined as a percentage of the existing power system's total capacity. Therefore, if the added wind plant is 10 MW and the existing power system's total capacity is 100 MW, the penetration level will be $[10 \div 100] \times 100\%$ or 10%. The penetration levels studied are 2% (55 MW), 5% (135 MW), 10% (270 MW), 15% (410 MW), and 20% (545 MW). These levels were created using both wind data sets, which resulted in two 55 MW wind plants, two 135 MW wind plants, two 270 MW wind plants, and so on; one created from the WP-1 data and one created from the WP-2 data. A COIPT is built for each of these ten wind plants using (23) with a resolution of 1 MW. For example, Table I represents part of the COIPT of a 55 MW wind plant using the power output data of WP-1.

As explained in Section III, when *classically* computing a wind plant's ELCC, the wind plant's COIPT must be combined to the existing system's COPT using (5) in order to obtain the potential system's COPT. Table II represents part of the COPT for the 2783 MW system, which results from adding a 55 MW wind plant to the existing 2728 MW system. Similar potential system's COPTs are built for the nine remaining wind plants.

Note that although the LOLE observation period is chosen to be a full year in this case study, the interannual variability of wind generation and its impact on a wind plant's ELCC could be captured by simply adjusting the COIPT in the calculations. Indeed, a monthly or peak load COIPT could be constructed with the appropriate wind plant's power output data. Then, using the corresponding load data when determining the existing system's m parameter, monthly or peak load ELCC estimates could be computed from (21) and the adjusted COIPT.

[4]The occurrence of a capacity outage of C_j is equivalent to the occurrence of a capacity in service, or power output, of $C_A - C_j$.

TABLE I
COIPT FOR A 55-MW WIND PLANT USING WP-1 POWER OUTPUT DATA AND A RESOLUTION OF 1 MW

Capacity Outage State C_j[MW]	**Individual Probability** p_j
0	0
1	0
2	0
3	0.00011416
4	0.0054795
5	0.010388
6	0.013128
...	...
50	0.02911
51	0.030023
52	0.028881
53	0.032763
54	0.040868
55	0.125

TABLE II
COPT FOR A 2783 MW POWER SYSTEM INCLUDING A 55 MW WIND PLANT USING WP-1 POWER OUTPUT DATA

Capacity Outage State x[MW]	**Cumulative Probability** $P(X_P > x)$
0	1
1	1
2	1
3	0.99996
4	0.99804
...	...
200	0.34358
201	0.34159
...	...
2780	1.1101×10^{-20}
2781	9.2703×10^{-21}
2782	6.9862×10^{-21}
2783	0

C. Load Model

A typical load duration curve consisting of a full year of hourly load data points was used in this analysis. This load demand displays the usual summer and winter peaks and was adjusted to ensure a LOLE of 1 day in 10 years (or 0.1 days per year) for our existing power system.

D. Results

Before applying (21) to estimate the ELCC of the ten wind plants described in Section V-B, the existing power system's m parameter must be determined graphically. Using (3), various new load duration curves are created with shifting percentages of $-20\%, -17.5\%, -15\%, \ldots 0\%, +2.5\%, \ldots +20\%$. The existent power system's LOLE is computed for these 16 new load duration curves in addition to the typical load duration curve. Table III presents the resultant LOLE values with their

TABLE III
EXISTING 2728 MW POWER SYSTEM'S LOLE
FOR VARIOUS LOAD DURATION CURVES

Load Duration Curve $L_c = L_t \pm c \cdot L_{t_{pk}}$ [MW]	**Annual peak load** $L_{c_{pk}}$ [MW]	**LOLE** [days per year]
$L_t - 20\% \cdot L_{t_{pk}}$	1570	0.00487
$L_t - 17.5\% \cdot L_{t_{pk}}$	1619	0.00766
$L_t - 15\% \cdot L_{t_{pk}}$	1668	0.01160
$L_t - 12.5\% \cdot L_{t_{pk}}$	1718	0.01761
$L_t - 10\% \cdot L_{t_{pk}}$	1767	0.02536
$L_t - 7.5\% \cdot L_{t_{pk}}$	1816	0.03561
$L_t - 5\% \cdot L_{t_{pk}}$	1865	0.05030
$L_t - 2.5\% \cdot L_{t_{pk}}$	1914	0.07082
L_t, **Typical Load Data**	**1963**	**0.10000**
$L_t + 2.5\% \cdot L_{t_{pk}}$	2012	0.14339
$L_t + 5\% \cdot L_{t_{pk}}$	2061	0.20964
$L_t + 7.5\% \cdot L_{t_{pk}}$	2110	0.30355
$L_t + 10\% \cdot L_{t_{pk}}$	2159	0.43665
$L_t + 12.5\% \cdot L_{t_{pk}}$	2208	0.61630
$L_t + 15\% \cdot L_{t_{pk}}$	2257	0.86541
$L_t + 17.5\% \cdot L_{t_{pk}}$	2306	1.16978
$L_t + 20\% \cdot L_{t_{pk}}$	2356	1.54865

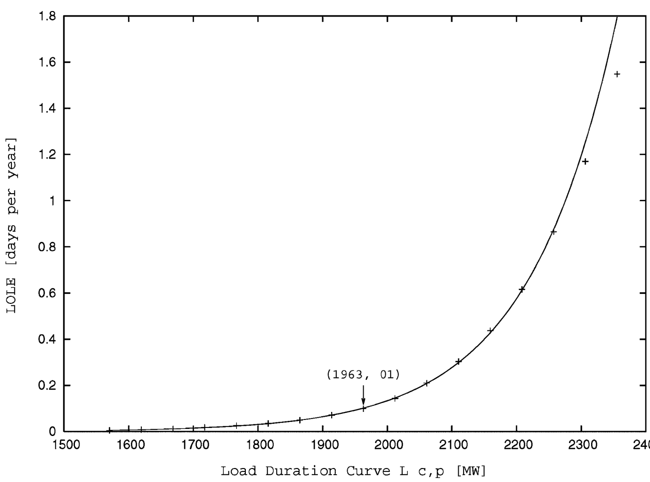

Fig. 1. Exponential relationship between the existing system's LOLE and a shifted increase or decrease in the typical load demand.

associated load duration curves. Although the peak load $L_{c_{\rm pk}}$ is used to represent the load duration curve L_c, the LOLE calculations are performed using all the relevant[5] hourly load data points, not only the peak load.

The results from Table III are graphed to obtain a relationship approximating the LOLE as a function of a shifted increase or decrease in the typical load demand. Fig. 1 illustrates this relationship between the existing system's LOLE and the annual peak load of each curve.

Using an exponential curve fitting tool in Fig. 1, the following relationship is established attributing a value of 7.30788×10^{-03} to the m parameter

$$\text{LOLE}_{L_{\rm pk}} = B \times e^{7.30788 \times 10^{-03} \times L_{\rm pk}}. \tag{25}$$

[5]The relevant data points are determined by the chosen LOLE evaluation period, which, in this case, is a full year.

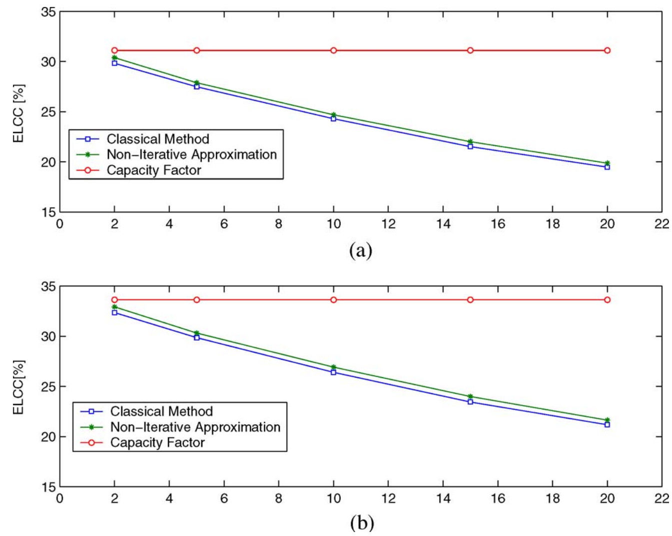

Fig. 2. Comparing ELCC results from the classical method, noniterative approximation, and capacity factor approximation for (a) wind plants created from WP-1 source data and for (b) wind plants created from WP-2 source data.

TABLE IV
COMPARISON OF ELCC RESULTS

WP-1 (All units [%])					
Wind Plant Penetration Level	**2**	**5**	**10**	**15**	**20**
ELCC Classical Method	29.8	27.5	24.3	21.5	19.5
ELCC Approximate Method	30.4	27.9	24.7	22.0	19.9
Percent Relative Error	2.0	1.4	1.6	2.3	1.9
Capacity Factor	31.1	31.1	31.1	31.1	31.1
Percent Relative Error	4.4	13.1	28.0	44.7	59.5
WP-2 (All units [%])					
Wind Plant Penetration Level	**2**	**5**	**10**	**15**	**20**
ELCC Classical Method	32.4	29.9	26.4	23.4	21.2
ELCC Approximate Method	32.9	30.3	26.9	24.0	21.6
Percent Relative Error	1.7	1.4	2.0	2.5	2.1
Capacity Factor	33.6	33.6	33.6	33.6	33.6
Percent Relative Error	3.7	12.4	27.3	43.6	58.5

Once the existing system's m parameter is determined, (21) can be applied to estimate the ELCC of the ten different wind plants given their respective COIPT (C_j and p_j values).

The resultant ELCC estimates must be compared to the classically computed ELCC values. To obtain these values, a COPT is built for each of the ten potential power systems using (5). Then, by an iterative process, (1) is solved for ΔL using the typical load demand described in Section V-C for all LOLE calculations. When the ΔL value of each wind plant is found, (2) is used to compute the actual ELCC values. All the ELCC results are illustrated in Fig. 2 where the wind plant's capacity factor is also included for comparison.

V. DISCUSSION

Table IV compares the ELCC results obtained from the case study. The noniterative method quite accurately approximates the classical method; it only slightly overestimates the ELCC by 1.4% to 2.5%. It gives consistent results for both sources of power output data (WP-1 and WP-2). On the other hand, the capacity factor approximation is only accurate at penetration levels of 2%, with a relative error of about 4%; it becomes quite inaccurate at higher penetration levels, reaching a relative error of nearly 60% for the wind plant penetration level of 20%. Therefore, although the capacity factor approximation is convenient because it does not require any reliability modeling, it is not a good overall ELCC approximation. When system generation and load data are available, the noniterative approximation is more appropriate; it produces more accurate ELCC estimates for all penetration levels while requiring minimal reliability modeling and computational efforts.

In summary, the advantages of using the noniterative approximation are the following:

1) The only LOLE calculations needed are the ones performed to determine the m parameter.
2) There is no need to build a generation reliability model, or COPT, for the potential power system that includes the additional wind plant.
3) There is no computationally-intensive iterative process to solve for ΔL.
4) Only a simple function using basic operations is needed to compute an accurate ELCC estimate.

Finally, if the actual ELCC value is needed, one could use the resultant ΔL estimates as a starting point to reduce the number of iterations required by the classical method.

VI. Conclusion

Inspired from Garver's approximation and based on well-known reliability concepts, a simple function was mathematically derived to compute ELCC estimates given the existing power system's graphically determined parameter as well as the wind plant's multistate probabilistic representation. Various wind plants of penetration levels between 2% and 20% were generated using two different sources of wind generation data. A power system of 2728 MW was created from 16 different conventional units and represented the existing power system considering wind generation expansion. Using the proposed noniterative method, the resultant ELCC estimates accurately approximated the classically computed ELCC values with relative errors of only 1.4% to 2.5%. Although the capacity factor approximation is a convenient method requiring no reliability modeling, it was shown to produce inaccurate ELCC estimates for wind plant penetration levels above 2% as relative errors reached nearly 60% for wind plant penetration levels of 20%. When system generation and load data is available, the noniterative approximation is an appropriate method that yields excellent ELCC estimates even at high penetration levels; it requires minimal reliability modeling and no computationally-intensive iterative process. As data become available, the authors will apply their method to other sources of variable output generation.

Acknowledgment

The authors would like to thank anonymous reviewers and Dr. J. J. Hasenbein, Associate Professor in Operations Research and Industrial Engineering, Department of Mechanical Engineering, The University of Texas at Austin for their insightful comments during the preparation of this manuscript.

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